Evaluation of Multilook Effect in ICA Based ICTD for PolSAR Data Analysis

Leandro Pralon, Nikola Besic, Gabriel Vasile, Mauro Dalla Mura, Jocelyn Chanussot

EVALUATION OF MULTILOOK EFFECT IN ICA BASED ICTD FOR POLSAR DATA ANALYSIS

Leandro Pralon[1], Nikola Besic[2], Gabriel Vasile[2], Mauro Dalla Mura[2], and Jocelyn Chanussot[2]

[1]*Brazilian Army Technological Center - Rio de Janeiro, Brazil, pralon@ctex.eb.br*
[2]*Grenoble Institute of Technology (Grenoble INP) - GIPSA-Lab, 38000 Grenoble, France*

ABSTRACT

Polarimetric incoherent target decomposition aims in accessing physical parameters of illuminated scatters through the analysis of target coherence or covariance matrix. In this framework, Independent Component Analysis (ICA) was recently proposed as an alternative method to eigenvector decomposition to better interpret non-Gaussian heterogeneous clutter (inherent to high resolution SAR systems). In this paper a Monte Carlo approach is performed in order to investigate the bias in estimating Touzi's Target Scattering Vector Model parameters when ICA is employed. Simulated data and data from the P-band airborne dataset acquired by the Office National d'tudes et de Recherches Arospatiales (ONERA) over the French Guiana in 2009 in the frame of the European Space Agency campaign TropiSAR are taken into consideration.

Key words: Polarimetric Incoherent Target Decomposition, Independent Component Analysis, Bias analysis.

1. INTRODUCTION

Polarimetric target decomposition is one of the most powerful and widespread tools for PolSAR image interpretation. The analysis of the interaction between the illuminated area and the transmitted waveform, to each polarimetric state of the latter, allows for a better prediction of the basic scattering mechanisms present on the scene, and to more efficiently propose classification, detection and geophysical parameter inversion algorithms.

Many methods have been proposed in the literature to both decompose an image pixel into basic target vectors and to correctly retrieve quantitative information from them (parametrization). Concerning the latter, Cloude and Pottier's parameters (entropy, alpha and anisotropy) [2] and Touzi's target scattering vector model [3] are the most employed ones, whose usefulness have already been demonstrated by several authors. Regarding the decomposition, the algorithms are mainly classified in either coherent, if they are based on the scattering matrix analysis, or incoherent if their interest lies in the Hermitian, semidefinite positive coherency or covariance matrix. Among the incoherent target decompositions (ICTD), the eigenvector based one manages to decompose an image pixel into the three most dominant scatters from the averaged coherence matrix. Furthermore, it has an intrinsic property that the derived scatters are orthogonal and uncorrelated, which for Gaussian clutters also means independence. The drawback of this kind of method emerge when the clutter is not Gaussian or not composed by orthogonal mechanisms, situations where the performance of the algorithm could be compromised.

In [4] a new strategy to polarimetric target decomposition was presented by incorporating the independent component analysis (ICA). The ICA is a blind source separation technique based on higher order statistical moments and cumulants whose utility has already been explored in many different research areas, such as wireless communications, feature extraction and brain imaging applications [1]. The results presented in [4] proved it to be a very promising area in polarimetry, mainly when non-Gaussian heterogeneous clutters (inherent to high resolution SAR systems) are under study. The theoretical potential in estimating similar entropy and first component, when compared to traditional eigenvector decomposition, but rather a second most dominant component independent with respect to the first one and unconstrained by the orthogonality introduces an alternative way of physically interpreting a polarimetric SAR image.

The referred method is briefly summarised in three main steps: data selection, based on the statistical classification of the POLSAR image; estimation of independent components and parametrization of the derived target vectors. As stated in [4], the principal drawback of the proposed method, is the size of the observation dataset, which has to be somewhat larger than the size of the sliding window used in the well established methods. This constraint lead the authors in [4] to use an unsupervised classification algorithm rather than relying on a very large sliding window, jeopardising the effectiveness of the method.

The use of a classification algorithm limits the performance of the method in the sense that the image is segmented in a priori defined number of classes with variable sizes, what can lead to either over or under estimations of the target vectors parameters.

Within this context, this paper considers a Monte Carlo simulation approach to investigate the tradeoffs existent in the selection of a sliding window size for various medias, simple ones composed by basic scatters such as helix, dipole, dihedral and trihedral and more complex ones like Surface, Double Bounce and Volume returns. The simulation procedure is similar to the one presented in [5] to evaluate the bias of multilook effect on Cloude and Pottier [2] parameters in eigenvector based polarimetric SAR decomposition. The seed mixing matrix, as well as the covariance matrix, for each of the aforementioned complex type of scatters are extracted from real data, more precisely, in this paper a P-band airborne dataset acquired by the Office National d'tudes et de Recherches Arospatiales (ONERA) over the French Guiana in 2009 is taken into consideration, while for the basic scatters analysis they are manually set. The main difference regarding the generation of the simulated data is that in [5] only Gaussian variables were addressed and no texture was considered, while in the present work the heterogeneous clutter is described by a multitexture (polarization dependent) model where texture is characterised by random variables.

This paper is organised in five sections. Section II presents the ICA approach proposed in [4] as an ICTD method, while in Section III a short review of Touzi's target scattering vector model [3] is performed. Section IV briefly describes the data simulation procedure, taking into account the multitexture model and the type of clutter analysed. In section V Touzi's estimated parameters are presented for different window sizes and compared to the values obtained using the traditional eigenvector decomposition. Finally in Section VI conclusions are drawn and future work possibilities are highlighted.

2. INDEPENDENT COMPONENT ANALYSIS (ICA)

The ICA approach is a blind source separation technique that aims, based on higher order statistical moments, in recovering statistical independent sources without having any physical background of the mixing process [7]. The derived parameters are stable both to polarization basis changes and rotations around the line of site and are not constrained to any orthogonality among them [4]. Let **x** be a set of observation vectors, then the mathematical model of ICA is written as

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

where **A** is the mixing matrix and **s** is the mutually independent sources vector. Analogously to eigenvector decomposition, each column of the estimated mixing matrix $\hat{\mathbf{A}}$ represents one of the most dominant mutually independent target vector present in the observed scene.

Once a stationary set of observed Pauli target vector is chosen, a pre-processing step, consisting in centering and whitening, is performed. Then a Non-Circular Complex Fast-ICA algorithm [8] is applied in order to estimate the mixing matrix $\hat{\mathbf{A}}$ and, consequently, the independent sources $\hat{\mathbf{s}}$. The Complex Fast-ICA algorithm can be applied with different criterions. In this paper we chose to employ the same approach as in [4], which is specifically suited to scenarios where sources may eventually present non-circular distributions [8]. The algorithm seeks to emphasise the Non-Gaussianity of the sources by maximising an arbitrary non linear contrast function whose extrema coincides with the independent component, which in the present work was chosen to be a logarithm function (described as the most appropriate in [4]), given by

$$G(y) = \log(0.05 + y) \tag{2}$$

The final step of the algorithm consists in de-whitening the estimated mixing matrix using the inverse of the operation performed during the pre-processing, assuring that, unlike eigenvector decomposition, the estimated components are not constrained to any orthogonality among them. A more complex discussion over the Non-Circular Complex Fast-ICA algorithm is out of the scope of the present work. For this purpose the reader is advised to read [4, 8].

The contribution of each source i to the total backscatering, evaluated as the squared l^2 complex norm of the corresponding mixing matrix column is given by

$$||\mathbf{A}_i||_2^2 = |A_{1i}|^2 + |A_{2i}|^2 + |A_{3i}|^2 \tag{3}$$

Entropy is then calculated in a similar manner as in eigenvector based decomposition. Likewise, the parameters for each target vector i are derived in an unchanged manner using either Touzi's TSVM or Cloude and Pottier parameters.

3. TOUZI'S PARAMETRIZATION

The scattering vector model derived by [3], for both symmetric and asymmetric targets is given by

$$e_T^{SV} = m|e_T|_m \cdot e^{j\phi_s} \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(2\psi) & -\sin(2\psi) \\ 0 & \sin(2\psi) & \cos(2\psi) \end{bmatrix} \cdot \begin{bmatrix} \cos(\alpha_s)\cos(2\tau_m) \\ \sin(\alpha_s)e^{j\phi_{\alpha_s}} \\ -j\cos(\alpha_s)\sin(2\tau_m) \end{bmatrix} \tag{4}$$

where each coherent scatter can be represented by four roll-invariant parameters α_s, τ_m, ϕ_{α_s} and m and by two roll variant parameters ϕ_s and ψ. In [10], Bombrun made a detailed investigation of the ambiguities in (4) and came up with the following relations

$$\begin{aligned} e_T^{SV}(\tau_m, \alpha_s, \phi_{\alpha_s}, m, \phi_s, \psi) &= e_T^{SV}(-\tau_m, \alpha_s, \phi_{\alpha_s} \pm \pi, m, \phi_s, \psi \pm \frac{\pi}{2}) \\ &= e_T^{SV}(-\tau_m, -\alpha_s, \phi_{\alpha_s}, m, \phi_s, \psi \pm \frac{\pi}{2}) \end{aligned} \tag{5}$$

In (4), target helicity, τ_m, is used for identifying its symmetric nature and is defined in the interval $[-\pi/4,\ \pi/4]$. The parameter α_s, defined in the interval $[0,\ \pi/2]$ represents the magnitude of the symmetric scattering type, while ϕ_{α_s}, ranging between $[-\pi/2,\ \pi/2]$, its phase. These three parameters allows for a complete and an unambiguous description of coherent scatters while ψ determines the target orientation angle, m is a measure of the maximum amplitude return and the phase ϕ_s is investigated only in interferometric applications.

4. MONTE CARLO SIMULATION APPROACH

The heterogeneous clutter is here described by a multitexture (polarization dependent) model and simulated under different assumptions regarding its composition: basic scatters and complex scatters (Surface, Double Bounce and Volume). Like the Spherically Invariant Random Vectors (SIRV) model [6], each m-dimensional observation vector is characterised as a product between the speckle and the texture, but unlike the latter, the textures are considered polarisation dependent [11]. Even though the product model (SIRV) considering polarisation independent texture is well accepted in SAR community, the discussion over its validity is still an open topic in research. High resolution systems and tropical forested area may present different texture among the channels and therefore the product model doesn't always hold under these circumstances [12, 13].

The multitexture model is a class of non-homogeneous Gaussian processes with random variance where each m-dimensional observation vector $\mathbf{x}$ is defined as

$$\mathbf{x} = \sqrt{\boldsymbol{\tau}} \cdot \mathbf{z} \tag{6}$$

where $\mathbf{z}$ is an independent complex circular Gaussian vector, characterising the speckle, with zero mean and covariance matrix of the form $[T] = \sigma_0 \cdot [M]$, such that $\mathrm{Tr}\{|M|\} = 1$ and σ_0 is the total power (span). In (6), $\boldsymbol{\tau}$ represents the texture, a positive random vector characterising the spatial variations in radar backscattering for each channel. The probability density function of the texture random variable is not explicitly specified by the model, therefore, in the present work, it is assume that they are independent and share the same statistical properties among channels (i.i.d.). Furthermore they are assumed Gamma distributed.

The Independent Component Analysis does not include the estimation of the covariance matrix itself, nevertheless, since, for comparison reasons, we perform the same simulations with the Eigenvector based decomposition, the coherence matrix estimator is also addressed. Therefore, as indicated in [6], the generalised maximum likelihood estimator of $[M]$ is the solution of the recursive equation given by

$$[\hat{M}]_{FP} = f([\hat{M}]_{FP}) = \frac{1}{N} \sum_{i=1}^{N} \frac{x_i x_i^H}{x_i^H [\hat{M}]_{FP}^{-1} x_i} \tag{7}$$

where x_i, $0 < i < N$ are the samples and N is the square of the window size.

Each simulation procedure, for a given window size and clutter type is repeated 1000 times and then the estimated parameters are averaged. For the first set of simulations the scattering mechanisms are assumed basic scatters and two scenarios are established: one containing orthogonal targets and the other containing non-orthogonal mechanisms. The Gamma distribution shape and scale parameters that characterises the texture are fixed and set to 1.95 and 0.51, respectively. They are used to generate a simulated texture vector $\tilde{\boldsymbol{\tau}}$. Afterwards, a complex normal distributed random vector $\tilde{\mathbf{z}}$, i.e., $\tilde{\mathbf{z}} \sim CN(\mathbf{0}, \mathbf{I})$ is generated. Finally, the simulated observation vector for each type of clutter is then given by

$$\tilde{\mathbf{x}} = \mathbf{A}\sqrt{\tilde{\boldsymbol{\tau}}} \cdot \tilde{\mathbf{z}} \tag{8}$$

The simulated dataset (8) is then used as input for both the Eigenvector decomposition and ICA decomposition.

Let us first investigate the behaviour of Eigenvector decomposition, hereafter also referred to as PCA (*Principal Component Analysis*) and ICA under the assumption that the heterogeneous clutter is composed by orthogonal targets: 60% of helix left screw, 30% of helix right screw and 10% of trihedral. The mixing matrix, in Pauli basis for such type of clutter [3] is given by

$$\mathbf{A} = \begin{bmatrix} 0.3162 & 0 & 0 \\ 0 & 0.3873 & 0.5477 \\ 0 & 0.3873j & -0.5477j \end{bmatrix} \tag{9}$$

where $j = \sqrt{-1}$ is the imaginary unit. The Entropy of such clutter is 0.8 while Touzi's roll invariant parameters are displayed in Table 1.

Table 1: Orthogonal mechanisms Touzi's parameters

	τ_m [deg]	α_s [deg]	ϕ_{α_s} [deg]
Helix left screw	45	45	0
Helix right screw	-45	45	0
Trihedral	0	0	0

Figure 1 presents the estimated Touzi's roll invariant parameters and entropy derived using ICA and eigenvector decomposition.

Note that both Eigenvector decomposition and ICA correctly derive the Touzi's parameters corresponding to the three components as well as the entropy. The convergence rate of both methods are similar and they even present the same behaviour with respect to the estimation of the α_s parameter of the third component. Regarding the Entropy, note that while suboptimal window sizes produce an under estimation of it when Eigenvector decomposition is used, if ICA is employed, suboptimal window sizes produces over estimation.

Next a scenario with non-orthogonal targets is addressed. The clutter is then composed by 60% of helix left screw,

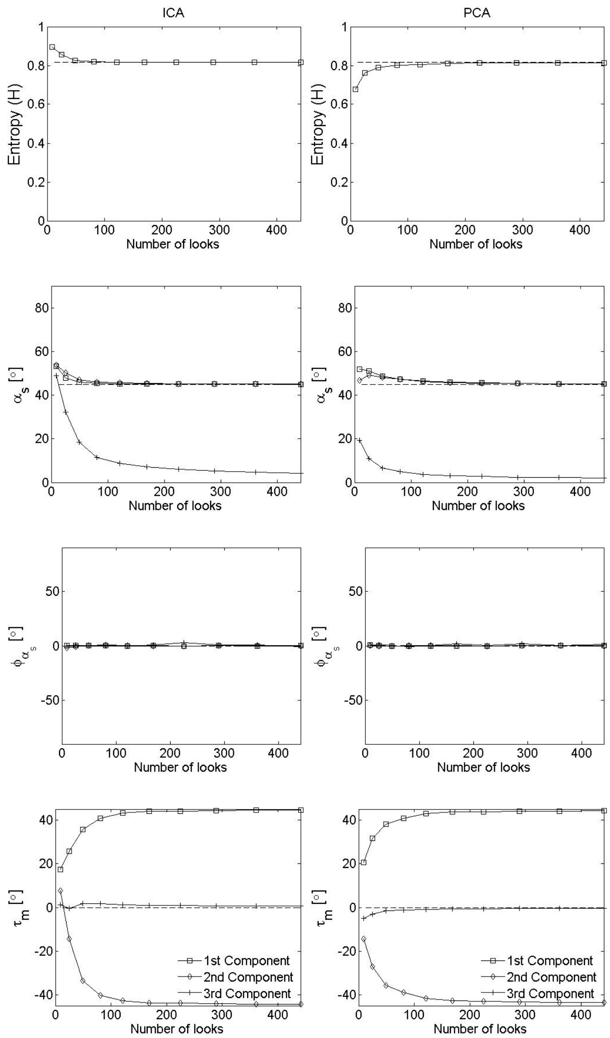


Figure 1: Entropy and Touzi TSVM parameters derived with ICA and Eigenvector polarimetric target decomposition (PCA) for a clutter composed by basic orthogonal mechanisms.

30% of dipole and 10% of dihedral. The mixing matrix, in Pauli basis, for such type of clutter is given by

$$\mathbf{A} = \begin{bmatrix} 0 & 0.3873 & 0 \\ 0.3162 & 0.3873 & 0.5477 \\ 0 & 0 & -0.5477j \end{bmatrix} \tag{10}$$

The Entropy of such clutter is also 0.8 while Touzi's roll invariant parameters are displayed in Table 2.

Table 2: Non-orthogonal mechanisms Touzi's parameters

	τ_m [deg]	α_s [deg]	ϕ_{α_s} [deg]
Helix left screw	45	45	0
Dipole	0	45	0
Dihedral	0	90	0

As expected, since Eigenvector decomposition has an intrinsic constraint that the estimated components are mutually orthogonal, it is unable to correctly derive the original mixing matrix, failing to estimate the contents of the heterogeneous clutter. On the other hand, ICA is not constrained to orthogonality therefore it successfully estimates the three components parameters. Figure 2 presents the results of ICA.

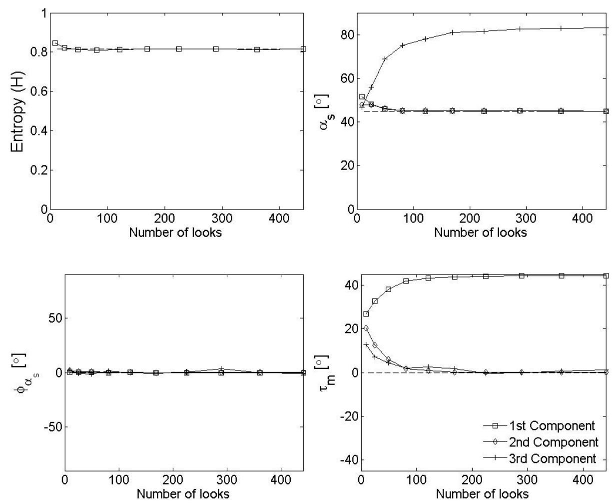
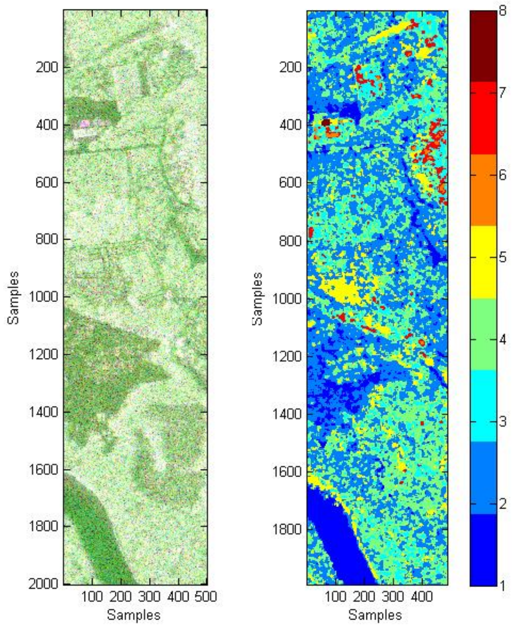


Figure 2: Entropy and Touzi TSVM parameters derived with ICA polarimetric target decomposition for a clutter composed by basic non-orthogonal mechanisms.

Note that the convergence rate of the estimated parameters, compared to a scenario with only orthogonal targets (see Figure 1) nearly doesn't change, concluding that the same window size can be used despite of the orthogonality of the scattering mechanisms.

Let us now address more complex type of targets, composed by either Surface, Double-Bounce or Volume scatters. The first step in the simulation procedure is to define the observation dataset from which the covariance matrix, the mixing matrix and the texture parameters will be estimated for each of the aforementioned mechanisms. In the present analysis the P-band airborne dataset acquired by Office National d'tudes et de Recherches Arospatiales (ONERA) over French Guiana in 2009 in the frame of the European Space Agency campaign TropiSAR is taken into consideration. A statistical classification algorithm is employed to discriminate the aforementioned classes in the scene under study. Figure 3 presents the referred area and the classification algorithm output.



(a) (b)

Figure 3: French Guiana area under study: (a) RGB image, Red (HH+VV), Green (HV), Blue (HH-VV); (b) Statistical classification algorithm output.

Each class was analysed using an H/α feature space in order to verify the ones that better corresponds to Volume, Double-Bounce and Surface scatters. Therefore samples corresponding to each class were extracted from the referred set and the mixing matrix, $\hat{\mathbf{A}}^c$, and covariance matrix, $[\hat{M}]^c_{FP}$, were estimated for each of the described classes ($c = volume, double-bounce, surface$) of mechanisms. An algorithm described in [9], initialised with the identity matrix, is used for the latter.

Figure 4 presents the results of the polarimetric decomposition using both ICA and Eigenvector decomposition (PCA).

Note that as well as reported in [5] Eigenvector decomposition presents the greatest bias in Entropy and α_s estimation for Volume type of clutters. The same happens for ICA ICTD, with a caveat, the bias in the estimation of the α_s parameter for Volume type of clutter using ICA is much greater than when Eigenvector decomposition is employed. Nevertheless the results obtained for ϕ_{α_s} and τ_m do not follow the same pattern. For ϕ_{α_s}, Surface presents the lower convergence rate, nevertheless the Bias of small window sizes in ICA is more harmful than in Eigenvector decomposition. On the other hand, for the helicity estimation, Double Bounce type clutters are the ones with lower convergence rate and similar Bias for both ICA and Eigenvector decomposition.

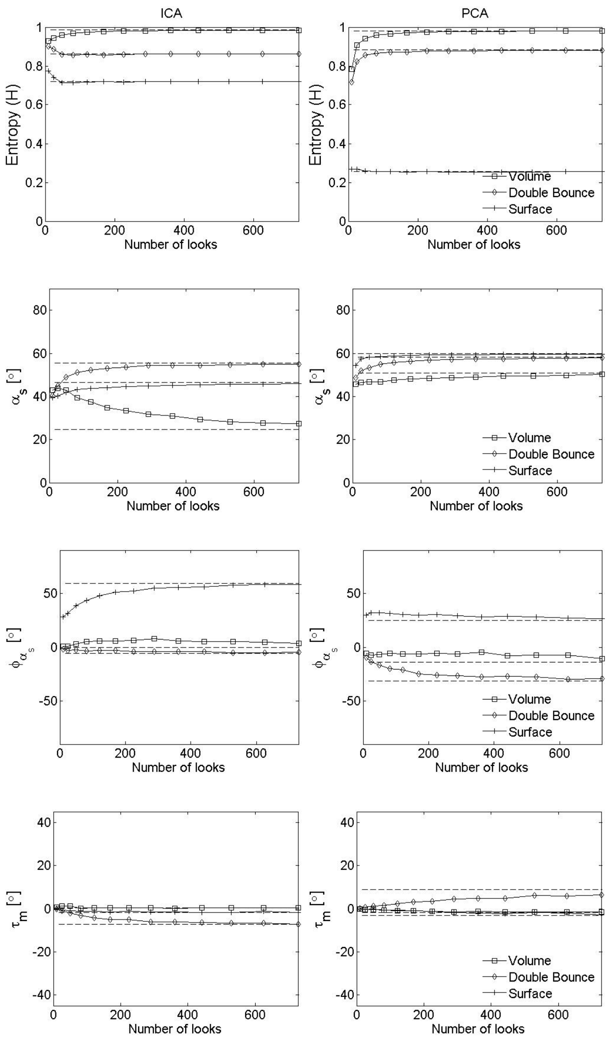


Figure 4: Entropy and Touzi TSVM parameters derived with ICA and Eigenvector polarimetric target decomposition (PCA) for complex clutter types: Surface, Double-Bounce and Volume.

5. CONCLUSION

This paper focused on addressing the main drawback of the employment of Independent Component Analysis in polarimetric target decomposition: the higher amount of samples needed. Based on simulated data we manged to better investigate the theoretical concepts and analyse the tradeoffs on the estimation of the entropy and Touzi's parameters caused by not sufficient number of samples.

It was shown that when the heterogeneous clutter is composed only by orthogonal mechanisms Touzi's parameters estimated using ICA are the same as the ones estimated using eigenvector decomposition. Furthermore, both Eigenvector decomposition and ICA present similar behaviour with respect to the convergence rate of the estimation, meaning that the same window size can be used for both methods. Nevertheless, in the derivation of the entropy, suboptimal window sizes will induce an over estimation when ICA is employed and an under estimation when Eigenvector decomposition is used. When the clutter is composed by non-orthogonal mechanisms, unlike Eigenvector decomposition, ICA successfully derive the basic scattering mechanisms without compromising its performance.

Simulations with complex type of scatters, Volume, Double-Bounce and Surface, whose characteristic were extracted from real data, showed some unexpected results. Even though both the entropy as well as Touzi's roll invariant parameters all converged using both ICA and Eigenvector decomposition, they did with varying convergences rates and Bias for small window sizes, therefore, creating a compromise in the settlement of the optimal window size.

Future works will continue on establishing theoretical background for the use of ICA in Incoherent Target Decomposition for PolSAR data, either analytically or empirically. Furthermore the new information provided by a second and third most dominant components different from the ones obtained with Eigenvector decomposition is still under analysis to new applications.

REFERENCES

1. A. Hyvrinen, J. Karhunen, and E. Oja, "Independent Component Analysis", John Wiley and Sons, 2001.
2. Cloude, S. R. and Pottier, E., "A review of target decomposition theorems in radar polarimetry", IEEE Trans. Geosci. Remote Sens., vol. 34, no. 2, pp. 498518, 1996.
3. Touzi, R., "Target scattering decomposition in terms of roll-invariant target properties", IEEE Trans. Geosci. Remote Sens., vol. 45, no. 1, pp. 7384, 2007.
4. Besic, N., Vasile, G., Chanussot, J., Stankovic, S. Polarimetric Incoherent Target Decomposition by Means of Independent Component Analysis, IEEE Trans. Geosci. Remote Sens., vol. 53, no. 3, pp. 1236-1247, 2015.
5. Lee, J., Ainsworth, L., Kelly, J.P., Lopez-Martinez, C. "Evaluation and Bias Removal of Multilook Effect on Entropy/Alpha/Anisotropy in Polarimtric SARDecomposition", IEEE Trans. Geosci. Remote Sens. October 2008.
6. G. Vasile, J. P. Ovarlez, F. Pascal, and C. Tison, "Coherency matrix estimation of heterogeneous clutter in high-resolution polarimetric sar images", IEEE Trans. Geosci. Remote Sens., vol. 48, no. 4, pp. 18091826, 2010.
7. P. Comon, "Independent component analysis: A new concept?",Signal Processing, vol. 36, pp. 287314, 1994.
8. A. Hyvarinen, "Fast and robust fixed-point algorithms for independent component analysis", IEEE Trans. on Neural Netw., vol. 10, no. 3, p. 626634, 1999.
9. E. Conte, A. DeMaio, and G. Ricci, "Recursive estimation of the covariance matrix of a compound-Gaussian process and its application to adaptive CFAR detection", IEEE Transactions on Image Processing, vol. 50, no. 8, pp. 19081915, 2002.
10. L. Bonbrum, "Dveloppement D'outils et de Mthodes de Tldtection Spatiale Optique et Radar Ncessaires la Haute Rsolution Spatiale", Ph.D. thesis, Institut Polytechnique de Grenoble, France, 2008.
11. T. Eltoft, S. N. Anfinsen, A. P. Doulgeris, "A Multitexture Model for Multilook Polarimetric Synthetic Aperture Radar Data", IEEE Trans. Geosci. Remote Sens., vol. 52, no. 5, pp. 2910-2919.
12. R. Touzi, W. M. Boerner, J.-S. Lee, and E. Lueneburg, A review of polarimetry in the context of synthetic aperture radar: Concepts and information extraction, Can. J. Remote Sens., vol. 30, no. 3, pp. 380407, 2004.
13. G. Vasile, N. Besic, A. Anghel, C. Ioana, J. Chanussot, "Sphericity of Complex Stochastic Models in Multivariate SAR Images", 2013 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Australia, 2013.
14. D.R Sheen, L.P. Johnston, "Statistical and spatial properties of forest clutter measured with polarimetric synthetic aperture radar (SAR)", IEEE Trans. Geosci. Remote Sens., vol. 30, no. 3, pp. 578-588.